Revista de Análisis Económico, Vol. 40, Nº 1, pp. 3-32 (Abril 2025)

MULTIDIMENSIONAL AND MONETARY POVERTY IN PERU: EVIDENCE OF THEIR EVOLUTION, DETERMINANTS, AND THE IMPACT OF THE PANDEMIC

POBREZA MULTIDIMENSIONAL Y MONETARIA EN PERU: EVIDENCIA DE SU EVOLUCION, DETERMINANTES Y EL IMPACTO DE LA PANDEMIA

NICOLE ARIANA CACERES BAUTISTA*
Banco de Crédito del Perú

DANTE A. URBINA**
Universidad de Lima

Abstract

The COVID-19 outbreak has left a profound economic aftermath, disrupting decades of consistent progress in poverty reduction in several countries. In this context, it is relevant to study the Peruvian economy since it experienced one of the highest COVID-19 mortality rates globally, its GDP declined by 11% and its monetary poverty rate rose to 30%, a situation not observed since 2010. Therefore, to better understand Peru's socioeconomic landscape after the pandemic, we construct a Multidimensional Poverty Index during the period 2019-2022 and compare it with monetary poverty using data sourced from the National Household Survey. We find that the latter was more volatile than multidimensional poverty. Employing logistic panel regressions, consistent patterns emerge in terms of the signs and statistical significance of the marginal effects for both poverty measurements across various weighting structures and poverty cutoffs. For instance, certain demographic groups, including rural women, those with only primary education, the unemployed and informal workers, exhibit a significantly heightened probability of experiencing both monetary and multidimensional poverty. The pandemic also increased the likelihood of experiencing both types of poverty across all scenarios considered. Conversely, individuals

* Area of Economic Studies, Banco de Crédito del Perú, Lima, Perú.
E-mail: nicolecaceres@bcp.com.pe. https://orcid.org/0000-0001-5170-9296
** Faculty of Business and Economic Sciences, Universidad de Lima, Lima, Perú.
E-mail: durbina@ulima.edu.pe. https://orcid.org/0000-0001-5403-9232

of mestizo ethnicity and those with higher education levels demonstrate a reduced likelihood of experiencing both types of poverty.

Keywords: *Multidimensional poverty, Weights, Poverty cutoffs, COVID-19, Peru.*

JEL Classification: *I32, O12.*

Resumen

La aparición de la COVID-19 ha dejado profundas secuelas económicas, interrumpiendo décadas de progreso constante en la reducción de la pobreza en varios países. En este contexto, es relevante estudiar la economía peruana, ya que experimentó una de las tasas de mortalidad por COVID-19 más altas del mundo, su PIB disminuyó 11% y su tasa de pobreza monetaria aumentó al 30%, una situación no observada desde 2010. Por tanto, para comprender mejor el panorama socioeconómico de Perú después de la pandemia, construimos un Índice de Pobreza Multidimensional durante el período 2019-2022 y lo comparamos con la pobreza monetaria utilizando datos provenientes de la Encuesta Nacional de Hogares. Encontramos que esta última fue más volátil que la pobreza multidimensional. Empleando regresiones logísticas de panel, surgen patrones consistentes en términos de los signos y la significancia estadística de los efectos marginales para ambas mediciones de pobreza mediante varias estructuras de ponderación y puntos de corte de pobreza. Por ejemplo, ciertos grupos demográficos, incluyendo mujeres rurales, aquellos solo con educación primaria, desempleados y trabajadores informales, exhiben una probabilidad significativamente mayor de experimentar pobreza monetaria y multidimensional. La pandemia también aumentó la probabilidad de experimentar ambos tipos de pobreza en todos los escenarios considerados. Por el contrario, las personas de etnia mestiza y aquellas con mayor nivel educativo presentan una menor probabilidad de experimentar ambos tipos de pobreza.

Palabras clave: *Pobreza multidimensional, Ponderaciones, Líneas de corte de pobreza, COVID-19, Perú.*

Clasificación JEL: *I32, O12.*

1. INTRODUCTION

Reducing poverty remains a crucial objective in both national public policies and international agreements. It not only takes the lead as the primary Sustainable Development Goal (SDG), but also holds relevance as a pervasive imperative across various domains (Santos *et al.*, 2015). As the United Nations (2023) points out, this goal assumes heightened importance in the current era, marked by a multitude of crisis, encompassing conflicts, climate change, the lingering aftermath of the COVID-19 pandemic, and other global challenges. If current patterns persist, 575 million individuals will remain in extreme poverty, and only one-third of nations will achieve a 50% reduction in their national poverty rates by 2030 (United Nations, 2023). The pandemic has triggered substantial setbacks in global health with a rise in deaths from tuberculosis and malaria compared to pre-pandemic levels. Education has also suffered devastating consequences, leading to learning losses in four out of five countries around the world. The economic aftermath is equally profound, disrupting decades of consistent progress in poverty reduction in several countries.

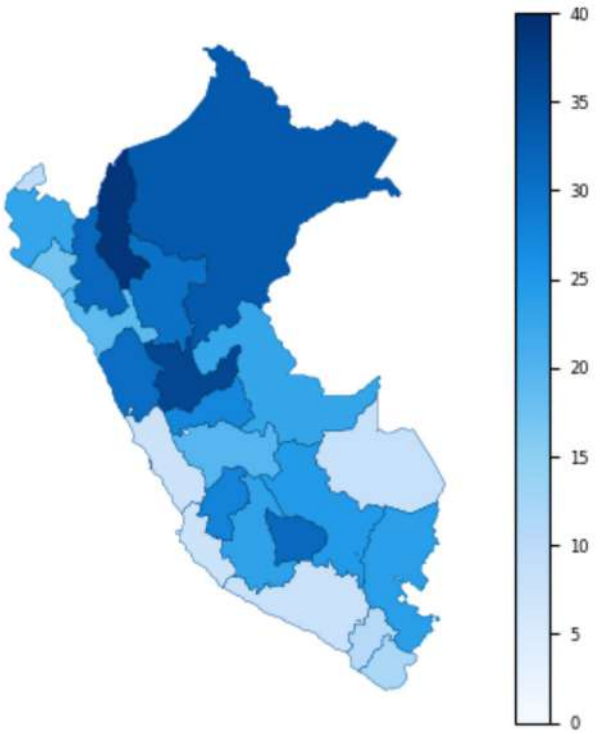
In particular, the Peruvian economy was especially hit by the global pandemic since it experienced one of the highest COVID-19 mortality rates globally and implemented rigorous confinement measures that severely affected the workforce, which is mainly engaged in the informal sector (World Bank, 2023). Consequently, this country experienced an 11% contraction in production in 2020, coupled with a rise in the monetary poverty rate to 30%, a figure not observed since 2010 (World Bank, 2023). Given this, it becomes imperative to comprehensively understand the magnitude of the threat posed by the pandemic in terms of reversing developmental gains.

In this context, it must be noted that Peruvian government agencies traditionally focus on monetary poverty measures (Vásquez, 2012). However, as Alkire and Fang (2019) point out, a critical step before policymaking involves reconsidering how poverty is measured, specifically, determining the metrics employed to identify and assist the impoverished. In this regard, the inclusion of deprivations in education, health, and living conditions within the Multidimensional Poverty Index (MPI) significantly enriches the diagnostic process. In fact, this has been recently recognized by the Peruvian Ministerio de Desarrollo e Inclusión Social (MIDIS, 2023) with the Supreme Decree No. 002-2023, which declares the development of an official measurement of multidimensional poverty a national priority. *Figure 1* provides a picture of the situation of multidimensional poverty in Peru in 2022, presenting data from the National Household Survey (ENAHO). Notably, poverty is particularly pronounced in the northern *sierra* (Andean region) and *selva* (rainforest), encompassing regions such as Loreto, which exhibits the lowest indices of provision of potable water, drainage, and primary education (Sociedad Nacional de Industrias [SNI], 2022). Conversely, poverty is less severe in the southern coast, where regions such as Arequipa and Moquegua, characterized by highly productive sectors like mining, metal mechanics, agroexportation, and alpaca textile production, are located (SNI, 2022).

Furthermore, Lima, the capital city, exhibits low levels of multidimensional poverty since it concentrates 59.4% of the Peruvian industrial apparatus, 42.8% of the total resources generated by the country, and holds the highest provision of public services and population (SNI, 2022). This clearly shows the high degree of centralization of the Peruvian economy.

FIGURE 1

SITUATION OF MULTIDIMENSIONAL POVERTY IN PERU, BY REGIONS (2022)



Note: Own elaboration.

As Alkire and Fang (2019) note, poverty has traditionally been assessed within the realms of income and expenditure, identifying individuals as poor if they lack sufficient funds to meet their essential needs. Thus, monetary data seems to offer a straightforward tool for policymakers engaged in monitoring and targeting poverty. However, from a policy standpoint, these measures fail to explain the underlying

reasons for poverty. Insufficient information or signals may render policies -such as cash transfers- inefficient since they do not address the root causes. In this sense, Sen (1999) argues that poverty reduction should not solely focus on monetary factors; instead, it should also consider health, education, and other dimensions, which are intrinsically valuable and instrumental for economic productivity. Consequently, following the capability approach, it must be considered that poverty involves various dimensions and should therefore be measured from a multidimensional perspective.

In addition to studies which only focus on the MPI construction (see Vásquez, 2012; Alkire & Santos, 2014; Alkire & Apablaza, 2016), there are also some empirical studies which analyze how personal characteristics and other factors influence the MPI. For instance, Betti *et al.* (2002) use a panel regression model with a fuzzy approach to explain poverty dynamics in England, while Coromaldi and Zoli (2012) employ a Non-Linear Principal Component Analysis (NLPCA) for Italy. Their findings coincide with the observation that individuals facing unemployment exhibit a heightened likelihood of experiencing multidimensional poverty. Regarding marital status, Coromaldi and Zoli (2012) additionally report that married individuals are less susceptible to this form of poverty. In contrast, Workneh and Eshete (2020) find that marriage increases the likelihood of experiencing monetary poverty. Similarly, Bautista (2018) and Alkire and Fang (2019) study the cases of the Philippines and China, respectively, and find that an increase in the head of the household's educational attainment significantly correlates with a reduction in overall household poverty. Meanwhile, Sánchez *et al.* (2022) find that individuals engaged in the informal sector are more prone to experiencing both multidimensional and monetary poverty for the case of Colombia. In terms of the absence of credit card ownership, Thanh *et al.* (2022) and Adetoro *et al.* (2023) find that it accentuates multidimensional poverty. On the other hand, Covarrubias (2023) finds that rural women face a significantly higher likelihood of experiencing both multidimensional and monetary poverty.

In this context, our paper contributes to the empirical literature by presenting evidence for the case of Peru. As stated above, this is relevant because it is a country that faced one of the highest global COVID-19 mortality rates and implemented stringent confinement measures, resulting in severe economic repercussions. Given this, our analysis explores the determinants of both multidimensional and monetary poverty through logistic panel regressions for the period 2019-2022. Our research distinguishes from other studies conducted on Peru since most of them focus on poverty from a monetary perspective for assessing the impact of economic policies on the poorest sectors (see Gambetta, 2007; Quispe Mamani *et al.*, 2022; Vela *et al.*, 2023) or, even when a multidimensional perspective is considered, they are mainly focused on the construction of the MPI and the explanation of its temporal dynamics (see Escobal, 2012; Vásquez, 2012; Clausen & Barrantes, 2020), but do not analyze its determinants with evidence from econometric regressions. In addition, despite some authors have compared monetary and multidimensional poverty in the Peruvian case (see Ruggeri, 1999; Urbina & Quispe, 2016), this study introduces a novel context: the pandemic.

2. METHODOLOGY

This section is based on the MPI proposed by Alkire and Foster (2011). In terms of notation, we consider a sample of n individuals (where $i = 1,...,n$) and a multidimensional space with dimensions (where $j = 1,...,d$). The achievement of individual i in dimension j is symbolized as a_{ij} Additionally, w_j represents the weight assigned to dimension j, so that $\sum_{j=1}^{d} w_j = 1$. Each dimension has its own deprivation cutoff z_j that represents the minimum achievement required for an individual or household to be considered non-deprived in that specific dimension. Furthermore, the "poverty cutoff" k determines whether an individual is classified as multidimensionally poor. The selection of this parameter involves normative considerations, as it sets the minimum threshold for the count of deprivations required for an individual or household to be deemed impoverished within the context under examination.

With this foundation, we follow a three-step process:

1) Calculation of the deprivation status of each individual for each dimension, which results in the formation of the binary variable g_{ij}. If the achievement level a_{ij} falls below the deprivation cutoff z_j, individual i is considered deprived in dimension j and g_{ij} is assigned the value 1; otherwise, it takes the value 0. These binary values are then consolidated into a nxd deprivation matrix, denoted as g^0.
2) Computation of a column vector c, where each element c_i represents the count of deprivations experienced by individual i, so that $c_i = \sum_j w_i g_{ij}$. If $c_i \leq k$, the individual is classified as multidimensionally poor. To refine the analysis, the deprivation matrix g^0 undergoes censorship, where deprivations corresponding to individuals not identified as poor are replaced with zeros, resulting in a modified matrix denoted as $g^0(k)$. Similarly, the vector of deprivation scores is adjusted such that for individuals identified as poor, $c_i(k)$ remains equal to c_i, whereas for those not classified as poor, it is set to zero.
3) Calculation of the MPI (M_0) as the product of the incidence, also known as the "poverty rate" or "headcount ratio" $H = \frac{q}{n}$, and the intensity of multidimensional poverty, that represents the average deprivation score among multidimensionally poor individuals $A = \left[\frac{1}{n}\sum_i c_i(k)\right]$. We focus on M_0 because it is better suited for dichotomous variables (Alkire & Fang, 2019), but it is important to note that there are also other measures developed by Alkire and Foster (2011) such as, for example, the adjusted poverty gap $M_1 = HAG = \mu\left(g^1(k)\right)$.
M_0 has many valuable analytical properties, including decomposability, replication invariance and symmetry. However, we primarily focus on decomposability.

Building on the framework introduced by Alkire and Fang (2019), we consider the entire population divided into m subgroups, which are mutually exclusive and collectively exhaustive. Consequently, the overall M_0 can be expressed as a weighted average of the M_0 values associated with these m subgroups, where the weights correspond to their respective population shares. Also, n is the population size and M^l_n is the adjusted headcount ratio within subgroup l, so that $M_0 = \sum_{l=1}^{m} \frac{n^l}{n} M_0^l$.

3. DATA SOURCES

We use the ENAHO dataset for the period 2019-2022, which is representative of Peruvian citizens since it covers both urban and rural areas across all regions of the country by means of a rigorous probabilistic, stratified, multistage, and independent sampling for each region (Instituto Nacional de Estadística e Informática [INEI], 2022b).

To monitor changes in population characteristics over time, the INEI implements a panel sample of households. In this approach, the same households, identified by unique codes, are re-interviewed annually (INEI, 2022b). If all members of a household are replaced by "new individuals," it is considered a new household, and the interview is conducted accordingly (INEI, 2015). In this context, to construct our panel dataset, we merge seven modules, namely: "Housing Characteristics", "Household Member Characteristics", "Education", "Health", "Employment and Income", "Household Assets" and "Summaries". These provide a comprehensive perspective on the multidimensional poverty landscape, offering insights both prior to and in the aftermath of the global pandemic.

Following Alkire and Fang (2019), to avoid the loss of sample and maintain a large sample size, we keep all observations in each wave even if this results in an unbalanced panel. Therefore, the total sample size consists of 60,089 households and 171,167 individuals across four survey waves. There are 15,322, 14,925, 14,694 and 14,946 households included in each year, respectively, and 46,401, 41,712, 40,401 and 42,653 individual respondents in each year, respectively. We consider the households exclusively in terms of permanent residents within them, so that the calculation of the deprivation matrix and the estimation of multidimensional poverty do not encompass visitors or non-permanent residents (Workneh & Eshete, 2020).

4. DIMENSIONS

The selection of dimensions to construct the MPI is a complex decision. Considering the intricacies involved, we use the three dimensions chosen by the United Nations

Development Program (UNDP) and the Oxford Poverty and Human Development Initiative (OPHI) to construct the global MPI, which include health, education, and living standards. However, we make some adjustments in terms of the indicators to better align with the specific context of Peru and the data at our disposal from the ENAHO. Information regarding the dimensions, indicators and cutoffs employed in our ENAHO-based MPI can be found in Table 1.

TABLE 1

DIMENSIONS, INDICATORS AND CUTOFFS OF THE ENAHO-BASED GLOBAL MPI

Dimension	Indicator	Deprived if	Relative weight
Education	Head of the household's education level	Head of the household has completed primary education or has an education level below that.	1/6
	Child attendance	The household includes at least one school-aged child (6-18 years old) who is not enrolled in and has not completed secondary education.	1/6
Health	Healthcare center attendance	The individual does not seek healthcare services when experiencing discomfort, illness, or an accident, due to financial constraints, distance from healthcare center or lack of insurance.	1/9
	Chronic illness	The individual suffers from a chronic illness (arthritis, hypertension, asthma, etc.).	1/9
	Health insurance affiliation	The individual does not have a private or public (ESSALUD) health insurance.	1/9
Living Standard	Cooking fuel	The household uses non-adequate fuels, such as wood or charcoal, for cooking.	1/21
	Drinking water	The source of drinking water is a tanker truck or similar, an open well, spring or *puquio*, river, lake, lagoon, etc.	1/21
	Drainage	The household lacks drainage connected to the public network.	1/21
	Electricity	The household does not have access to electricity.	1/21
	Floor	The household has a soil or sand floor.	1/21
	Assets	The household owns less than half of the following assets: radio, video recorder, electric iron, blender, television, DVD, computer/laptop, gas stove, telephone, refrigerator/freezer, washing machine, microwave oven, sewing machine, bicycle, car, motorcycle, tricycle, *mototaxi* or truck.	1/21
	Internet access	The household does not have an Internet connection (fixed wireless access or mobile broadband).	1/21

Note: Own elaboration.

As depicted in *Table 1*, our MPI incorporates two education-related indicators. We first evaluate whether the head of the household has completed primary education or possesses an education level below that threshold (see Bautista, 2018). Additionally, we examine whether the household includes at least one school-aged child who is neither enrolled in nor has completed secondary education. In this context, we use children's school attendance as a measure of their exposure to a learning environment and, following UNESCO (2010) and Santos (2019), consider that if a child is not attending school, all household members are categorized as deprived in the school attendance indicator.

Regarding the health dimension, there are three indicators. Firstly, we evaluate whether an individual refrains from seeking healthcare services when confronted with discomfort, illness, or an accident, due to factors like financial constraints, distant healthcare centers, or lack of insurance coverage (see Khan *et al.*, 2020; Gallardo, 2022). Secondly, we examine whether the individual suffers from chronic illness (see Coromaldi & Zoli, 2012). Lastly, we consider if an individual has a health insurance affiliation (see Gallardo, 2022).

The standard of living dimension encompasses seven indicators which, although serve as means rather than ends in themselves, play a crucial role in achieving dimensions of human development that hold intrinsic importance (Sen, 1999). For instance, the lack of access to clean drinking water, safe cooking fuel, and proper sanitation facilities could have detrimental effects on health (Alkire & Foster, 2011). Moreover, access to electricity and the quality of flooring material are fundamental indicators of housing quality. The assets indicator assesses whether individuals possess durable goods like telephones, televisions, or refrigerators, reflecting their overall standard of living. Also, the inclusion of Internet access is essential, particularly considering the COVID-19 outbreak, as it became a critical tool for working from home and accessing online education.

In addition, following the poverty line approach employed by the INEI (2023), we incorporate monetary data into our analysis to assess unidimensional poverty and compare it to multidimensional poverty. To obtain monthly adult-equivalent measures, we divide by 12 and by the number of household members over 14 who receive earnings. Next, in line with the INEI's (2022a) methodology, we adjust the nominal values using a base year and specific geographical scope. Specifically, we apply the average Consumer Price Index (CPI) for the eight major consumption groups by departments for 2022 and use Metropolitan Lima (Peru's capital city) as the reference point. This standardizes the values to the average prices of Metropolitan Lima in 2022. Finally, we generate a dichotomous variable for monetary poverty, assigning a value of one if the real monthly adult-equivalent measure falls below the poverty line for each year, and zero otherwise. Poverty lines have also been adjusted by the number of household income earners, inflation, and the geographical deflator.

5. WEIGHTS, CUTOFFS, AND ROBUSTNESS

Adhering to the global MPI methodology, we allocate one-third of the weight to each of the three dimensions – education, health and living standards. Additionally, within these dimensions, we maintain equal weight for each individual indicator. Consequently, an individual is categorized as multidimensionally poor if they experience deprivation in at least one-third of the weighted indicators. Thus, we adopt a poverty cutoff of 33%.

Nevertheless, we also conduct a robustness analysis, as suggested by Alkire and Santos (2014), Alkire and Fang (2019) and Alkire *et al.* (2019), by allocating 50% of the relative weight to one of the three dimensions and distributing 25% to each of the other two. Furthermore, we explore alternative poverty cutoffs and, following Alkire and Apablaza (2016) and Thusitha *et al.* (2019), consider the values of 30% and 35% to assess the validity of our results.

6. EVOLUTION OF MULTIDIMENSIONAL POVERTY AND ITS INDICATORS

Table 2 provides insight into the trends of multidimensional poverty, revealing a relatively stable pattern in contrast to the more volatile nature of monetary poverty. This divergence can be attributed, as suggested by Alkire and Fang (2019), to the composition of indicators within the multidimensional poverty framework. Many of these indicators, such as asset ownership and adult education, are considered relatively stable over time. In contrast, individual income and expenditure fluctuates annually for each person and is significantly influenced by the prevailing social and economic environment, including events like the global pandemic.

When assessing the prevalence of multidimensional poverty using the 33% cutoff, there was a slight increase within the Peruvian population, rising from 27.56% in 2019 to 27.75% in 2020. A similar upturn can be observed in alternative multidimensional poverty measurements using the 30% and 35% thresholds, which increased from 35.67% to 36.67% and from 25.12% to 25.43%, respectively. This pattern of a modest rise in the percentage of individuals experiencing multidimensional poverty due to the COVID-19 outbreak is not unique to Peru. For instance, Mexico experienced a slight rise in the percentage of individuals facing multidimensional poverty between 2018 and 2020, with rates increasing from 41.9% in 2018 to 43.9% in 2020 (Galindo *et al.*, 2022). In fact, there are also cases of a reported decrease during the pandemic such as that of Paraguay where the percentage of multidimensionally poor population decreased from 26.75% in 2019 to 24.93% in 2020 (Cuenca & Camargos, 2022). This decline can be attributed to the significant role played by social programs in mitigating the adverse effects of the COVID-19 outbreak, particularly in addressing deprivations related to inadequate sanitation practices, limited access to waste disposal services, and ensuring access to healthcare for sick or injured individuals.

In this sense, Alcázar *et al.* (2022) highlight the active involvement of MIDIS and other social assistance programs in the Peruvian government's response to the pandemic. Within this context, three primary social protection strategies were implemented. The first strategy involved cash transfers, commonly known as *bonos*, which included programs like *Bono Yo Me Quedo en Casa*, *Bono Rural* and *Bono Familiar Universal*. The second strategy focused on the distribution of food baskets, known as *canastas*, designed to assist vulnerable households and those facing food insecurity due to the loss of employment and income. Lastly, adaptations were made to existing social programs, such as *Qali Warma* and *Cuna Más*, to address the evolving needs and challenges brought about by the COVID-19 outbreak.

In contrast, monetary poverty experienced a notorious increase, climbing from 20.77% to 27.06% during the same period, reaching a level not seen since 2010 according to the World Bank (2023). This rise in monetary poverty could partially be linked to the fact that over 75% of the Peruvian population is engaged in the informal sector (OECD, 2023). In this sense, individuals who work in the informal economy lack labor protection and social security, rendering them vulnerable during economic downturns such as the pandemic, particularly when their access to savings and credit is constrained (Gwavuya, 2020; OECD, 2023). Relying on daily earnings, they were substantially affected by the quarantines, leading to an abrupt halt in income inflows. This is precisely one of the reasons why COVID-19 has a more pronounced impact on monetary poverty rather than on multidimensional poverty, where indicators tend to exhibit relative stability. For instance, if a person lacked access to drinking water before the pandemic, it is likely that this deprivation persists during and after the COVID-19 outbreak.

TABLE 2

PERCENTAGE OF THE POPULATION IN POVERTY AT DIFFERENT CUT-OFFS BY MEASURE OF POVERTY AND YEAR

k cutoff	Multidimensional poverty							
	2019		2020		2021		2022	
	%	95% C.I.	%	95% C.I.	%	95% C.I.	%	95% C.I.
30	35.67	[35.25 – 36.10]	36.67	[36.22 – 37.12]	35.48	[35.02 – 35.94]	33.46	[33.03 – 33.88]
33 (*)	27.56	[27.16 – 27.96]	27.75	[27.34 – 28.16]	27.50	[27.07 – 27.93]	25.96	[25.55 – 26.38]
35	25.12	[24.72 – 25.51]	25.43	[25.02 – 25.83]	24.81	[24.39 – 25.23]	23.48	[23.06 – 23.91]
MP	20.77	[20.41 – 21.14]	27.06	[26.65 – 27.48]	23.07	[22.66 – 23.49]	25.28	[24.84 – 25.71]

Note: Own elaboration. (*) Baseline model. MP: Monetary poverty. The MPI and MP estimators are calculated using the bootstrap sample. The resampling is replicated 1,000 times following Alkire and Shen (2017).

Table 3 presents the headcount ratios for all indicators, shedding light on the impact of the COVID-19 outbreak. Notably, the percentage of individuals relying on non-adequate fuels, such as wood or charcoal for cooking, increased from 34.78% in 2019 to 39.61% in 2020. Similarly, the proportion of people suffering from chronic illnesses rose from 45.69% to 48.86%. Furthermore, the deprivation ratio of child attendance experienced an increase from 2.66% to 2.96%. In this regard, it is worth highlighting that the Instituto Peruano de Economía (2021) reported that more than 400,000 students stopped attending classes in 2020 due to the ongoing health crisis.

Nevertheless, these factors contributing to the rise in multidimensional poverty in the Peruvian population are somewhat balanced by a decrease in other indicators. For instance, the percentage of individuals refraining from seeking healthcare due to financial constraints or a lack of health insurance declined from 11.42% to 8.05%. Additionally, it is worth emphasizing the substantial decrease in the percentage of individuals lacking Internet access, which dropped significantly from 67.90% in 2019 to 48.15% in 2022. This underscores the heightened importance of Internet connectivity for remote work, education, and social interactions during periods of lockdown.

TABLE 3

UNCENSORED HEADCOUNT RATIO OF EACH INDICATOR IN 2019-2022 (%)

Indicator	2019	2020	2021	2022
Head of the household's education level	15.28	15.95	17.02	15.57
Child attendance	2.66	2.96	2.57	2.84
Healthcare center attendance	11.42	8.05	9.13	10.54
Chronic illness	45.69	48.86	50.87	49.95
Health insurance	99.60	99.72	99.78	99.77
Cooking fuel	34.78	39.61	39.59	39.19
Drinking water	14.18	12.75	13.19	13.90
Drainage	41.28	41.64	42.08	42.80
Electricity	6.83	6.16	6.89	6.27
Floor	31.76	31.89	29.65	30.38
Assets	72.90	67.15	76.25	86.34
Internet access	67.90	64.02	53.09	48.15

Note: Own elaboration.

7. INDEPENDENT VARIABLES

As presented in Table 4, the independent variables are mainly related to the individual attributes of the household head, encompassing factors such as education level (three dummy variables), age, gender, marital status, and ethnicity (two dummy variables). Following Chen and Wang (2015), we assume that household members

TABLE 4

DESCRIPTIVE STATISTICS OF THE SURVEY DATA

	Variable	Description	Descriptive statistics
Dependent variables	Multidimensional poverty	1 = if multidimensionally poor, 0 = if not multidimensionally poor	27.19%
	Monetary poverty	1 = if monetary poor, 0 = if not monetary poor	23.97%
Independent variables	Rural woman	1 = if individual is a woman and lives in a rural area, 0 = otherwise	19.71%
	Indigenous ethnicity	1 = if by heritage and costumes the person considers himself to be quechua, aymara, native or belonging to another indigenous culture, 0 = otherwise	29.15%
	Mixed-race (mestizo)	1 = if by heritage and costumes the person considers himself to be mixed-race, 0 = otherwise	39.38%
	Primary school	1 = if last educational level approved by the individual is primary school, 0 = otherwise	44.94%
	University/ technical school	1 = if last educational level approved by the individual is university/ technical school (completed), 0 = otherwise	10.73%
	Master/ PhD	1 = if last educational level approved by the individual is a master's degree or PhD, 0 = otherwise	0.94%
	Public education	1 = if public education, 0 = if private education	78.52%
	Unemployment	1 = if individual is unemployed, 0 = otherwise	3.27%
	Informal sector	1 = if works in the informal sector, 0 = if works in the formal sector	49.88%
	No credit card	1 = if individual does not own a credit card, 0 = otherwise	19.77%
	Before pandemic	1 = if year is 2019, 0 = otherwise	27.11%
	COVID-19 outbreak	1 = if year is 2020, 0 = otherwise	24.37%
	After pandemic	1 = if year is 2021, 0 = otherwise	23.60%
	Male	1 = if male, 0 = if female	45.97%
	Married	1 = if married, 0 = if not married	24.18%
	Age	Age in years completed	38.79 (mean)
	Age squared	Age squared	1994.35 (mean)

Note: Own elaboration.

share resources and common characteristics, such as the area of residence. In turn, we incorporate variables that capture the employment status of the head of the household, differentiating between formal and informal sectors, as well as ownership of a credit card. Additionally, we introduce three temporal dummy variables to capture the impact of the COVID-19 outbreak, as well as the period immediately before and after. We do not include a dummy variable for the year 2022 to avoid perfect collinearity.

8. RESULTS

Comparison between multidimensional poverty and monetary poverty

Our analysis primarily focuses on variables related to household and head of the household characteristics. To assess the differences between monetary and multidimensional poverty, we use a panel logit model. Specifically, we opt for random effects, as the likelihood-ratio (LR) test of $\rho = \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\varepsilon^2}$, which represents the proportion of the total variance attributed to the panel-level variance component, indicates significant variance across individuals, making random effects more appropriate than the pooled estimator (StataCorp, n.d.). For further details on this test, refer to the Appendix A. Additionally, as outlined by Torres-Reyna (2007), Kohler and Kreuter (2012), and Alkire and Fang (2019), random effects models offer an advantage over fixed effects models by allowing the inclusion of time-invariant variables. In the fixed effects models, these characteristics are absorbed by the intercept, preventing biased estimates if they are omitted. This makes them particularly attractive for studying the causes of changes within individuals. However, they are not suitable for investigating time-invariant causes of the dependent variables, such as gender, ethnicity, and urban-rural classification in this case.

Table 5 displays the marginal effects obtained from our panel logit model estimation. Given this, we find that rural women face a significantly higher likelihood of experiencing both multidimensional and monetary poverty, particularly the former. This aligns with the findings of Covarrubias (2023), who suggests that this could be attributed to the limited access to essential health, education and housing services in rural areas, and Peng (2022), who highlights that deep-rooted gender norms about the division of labor place rural women at a disadvantage concerning asset ownership, resource control, and participation in decision-making processes related to family and production activities. As Agarwal (1989) points out, rural poverty disproportionately affects women due to internal disparities in the allocation of essential resources and domestic responsibilities within these households. For instance, when a town lacks access to drinking water, women often undertake arduous journeys on foot, carrying heavy loads to bring water to their homes (Banerjee & Duflo, 2011), which leaves

TABLE 5

MARGINAL EFFECTS FROM PANEL LOGIT ESTIMATION FOR MULTIDIMENSIONAL AND MONETARY POVERTY

	Dependent variable			
	Multidimensional poverty		Monetary poverty	
	β	SE	β	SE
Rural woman	11.3009*	0.5095	5.7842*	0.6190
Indigenous ethnicity	3.5578*	0.3394	0.6760	0.4323
Mixed-race (mestizo)	-1.7122*	0.3334	-5.5001*	0.4479
Primary school	37.2261*	0.1795	11.6566*	0.3750
University/ technical school (completed)	-7.0403*	0.5092	-15.6917*	0.7766
Master/ PhD	-13.9078*	2.1969	-38.5496*	5.1310
Public education	0.6444	0.3941	0.0283	0.4901
Unemployed	3.3617*	0.8321	8.0888*	1.1327
Informal sector	6.9108*	0.3129	7.5385*	0.4408
No credit card	9.1483*	1.6286	29.4791*	4.1378
Before pandemic	-7.7328*	1.6288	-32.7834*	4.1360
COVID-19 outbreak	0.8531*	0.3332	0.9115*	0.4372
After pandemic	-0.1711	0.3313	-2.5772*	0.4407
Male	4.1246*	0.3221	7.9658*	0.4599
Married	-1.0080*	0.2871	3.6679*	0.3804
Age	-0.0789	0.0506	-0.9379*	0.0647
Age squared	0.0025*	0.0005	0.0058*	0.0006

Note: *p<0.05. SE: Standard Error.

them in a vulnerable position. In this way, echoing Vásquez (2012), it can be said that, on a national scale in Peru, poverty wears the face of a rural woman.

Concerning ethnicity, individuals who identify with an indigenous background exhibit an increased likelihood of experiencing multidimensional poverty. Conversely, those who self-identify as mestizos or of mixed-race experience a diminished probability of encountering either multidimensional or monetary poverty. Nevertheless, it is necessary to recognize that "mestizo" represents a broad category encompassing diverse ethnicities. As suggested by Oboler and Callirgos (2015), most Peruvians choose to identify as mestizos to avoid extreme classification, since identifying as white could potentially evoke feelings of guilt given its association with the upper class, privilege, and abuse, while identifying as indigenous could be linked to perceptions of ignorance, lower prestige, and other stereotypes.

When considering education level, households led by individuals who have only completed primary school face a higher risk of experiencing both multidimensional

and monetary poverty, with a more pronounced effect on the former. However, as the household head's educational attainment increases, there is a notable impact on reducing overall household poverty, consistent with the findings of Bautista (2018) and Alkire and Fang (2019). Higher education, such as university or technical schooling, has an important role in contributing to poverty reduction. Nevertheless, it is important to note that the effect of more advanced education levels, like postgraduates, is even more substantial, since individuals with a master's or PhD degree experience a 14% and 39% lower likelihood of facing multidimensional and monetary poverty, respectively.

On the other hand, the type of educational institution, whether public or private, has no significant impact on the likelihood of experiencing either multidimensional or monetary poverty. This finding is in line with the work of Marcos and Vásquez (2018), who highlight the wide diversity in private education offerings depending on the socioeconomic conditions of the students and their families. Consequently, as tuition costs increase, academic outcomes tend to be better. Conversely, in the case of more affordable private schools, the academic performance of students is often similar or even lower than that of their peers in public schools. Therefore, this is a complex phenomenon that depends on various factors such as the socioeconomic conditions of the households.

Regarding employment status, our results indicate that individuals facing unemployment have a higher probability of experiencing both multidimensional and monetary poverty, particularly the latter. This aligns with the findings of Betti *et al.* (2002), Coromaldi and Zoli (2012), and Corcoran and Hill (1980), who argue that this is because unemployment results in significant economic hardships not only for the household head but also for other members of the household. In this way, beyond the direct link between unemployment and poverty due to the loss of income, Hinteregger (2017) emphasizes additional channels that perpetuate the poverty cycle since the unemployment of parents places a heavy burden on children, increasing their likelihood of dropping out of school to enter the workforce, engaging in criminal activities, and diminishing the chances of securing employment in the future. Also, it is important to note that unemployment could negatively affect the health dimension since unemployed people tend to experience anxiety and depression (Norström *et al.*, 2019).

In the realm of informality, our findings indicate that individuals engaged in the informal sector are more prone to experiencing both multidimensional and monetary poverty, aligning with the results of Sánchez *et al.* (2022), who study the case of Colombia. As elucidated by Canelas (2018), this phenomenon can be attributed to the prevalent poor quality of a substantial portion of informal employment in Latin American countries. Additionally, those involved in the informal sector typically exhibit lower educational attainment and receive lower wages, reinforcing the notion that these workers might lack viable alternatives to participate in the formal sector. Moreover, informal jobs are often characterized by low productivity and lack of safety nets, leaving individuals vulnerable to income loss during economic downturns (Gwavuya, 2020). Also, it must be noted that informal employment is often related

to informal housing, overcrowding, and lack of basic services (Simiyu *et al.*, 2018). However, it is worth noting that, while informal employment tends to be a last resort for low-skilled workers, it may also constitute a voluntary choice for individuals with higher education and entrepreneurial inclinations (Canelas, 2018).

Concerning the absence of credit card ownership, we find that it accentuates multidimensional poverty, aligning with the results obtained by Adetoro *et al.* (2023) and Thanh *et al.* (2022) for the cases of South Africa and Vietnam, respectively. This is based on the premise that credit facilitates household investments in various income-generating ventures. Particularly, Thanh *et al.* (2022) note that individuals in the working-age population using debit or credit cards are less prone to experiencing multidimensional poverty. In this sense, Yang *et al.* (2021) point out that credit constraints from formal financial institutions have a substantial negative impact on individuals' health, especially among rural residents. Similarly, regarding the impact on monetary poverty, our results indicate that the absence of credit card ownership is associated with an increased likelihood of experiencing it, which aligns with the empirical findings of Al-Mamun and Mazumder (2015). However, it is important to consider the dual nature of credit cards, as suggested by Fuentes (2014). While they serve as a financial safety net in emergencies, offering an accessible line of credit, they also pose a risk of encouraging imprudent or excessive purchases that surpass an individual's capacity to timely repay the incurred debt, particularly among low-income groups.

Additionally, our results indicate an elevated probability of facing both multidimensional and monetary poverty during the COVID-19 outbreak. Nevertheless, it is crucial to note that the impact on vulnerabilities varies across different dimensions. In this sense, Lin *et al.* (2021) note that the pandemic had the most significant influence on health deprivation vulnerability in rural China, while it did not affect vulnerability to material deprivation; instead, the latter was mitigated through government assistance and support provided to farmers. Also, it is crucial to recognize that the health threats posed by the coronavirus and its transmission are intricately connected to pre-existing conditions (Gwavuya, 2020). Moreover, widespread job losses or reduced income inflows during the pandemic led to challenges in meeting essential household expenses, including those relating to food, medical care and rent (Center on Budget and Policy Priorities, 2022). In this context, it is noteworthy that the COVID-19 outbreak exerts a more substantial effect on monetary poverty rather than on multidimensional poverty. This is because the indicators constituting the MPI, such as access to drinking water and drainage facilities, tend to remain relatively stable over time, in contrast to monetary poverty, which fluctuates during economic downturns, particularly affecting informal workers lacking labor protection and social security (Gwavuya, 2020; OECD, 2023). To see interactions with the dummy variable for the year 2020 and their effects on both multidimensional and monetary poverty, see Appendix B.

Additionally, it is important to note that individuals were less likely to experience both multidimensional and monetary poverty before and after the pandemic, but that

this probability was greatly reduced over time. For example, household heads had a 33% lower likelihood of experiencing monetary poverty in 2019, while this probability decreased to only 3% in 2021. This highlights the lingering aftermath of COVID-19 outbreak, which has persisted even after the emergency state ended and economic activities resumed (World Bank, 2023).

In the comparison between female-headed households and their male-headed counterparts, the latter are more prone to experiencing both multidimensional and monetary poverty, which is consistent with the results of Alkire and Fang (2019). In any case, it must be considered that, as Muñoz *et al.* (2018) point out, the differences in poverty rates between female- and male-headed households represent a multifaceted phenomenon that cannot be solely attributed to gender-based variations in earning, employment prospects, or resource management.

In terms of marital status, our analysis indicates that married household heads are less prone to experiencing multidimensional poverty compared to widows, divorced individuals, or singles, aligning with the findings of Coromaldi and Zoli (2012). This phenomenon could be attributed to the heightened financial distress and loneliness experienced by those who are not married, highlighting the potential protective effect of marriage in these dimensions (Olarinde *et al.*, 2020). Conversely, our results reveal that marriage increases the likelihood of experiencing monetary poverty, a pattern consistent with the findings of Workneh and Eshete (2020), which could be due to the fact that marrying without addressing underlying financial issues may not lead to improved outcomes (Coontz & Folbre, 2002).

When examining the age of the household head, it is important to note that for monetary poverty the impact of age is not linear. Instead, poverty levels decrease as the age of the household head increases up to a certain point, beyond which poverty levels start to rise with advancing age, as found by Alkire and Fang (2019). In this sense, as the United Nations Department of Economic and Social Affairs (2015) points out, advancing age poses a considerable risk of entering or persisting in poverty, as individuals often reduce their working hours or retire due to health concerns. Even for those who wish or need to extend their working years, their wages tend to diminish. Moreover, across many countries, the absence of robust social protection systems with extensive coverage and substantial benefits means that the financial resources, including assets and savings, prove inadequate to ensure a secure and sufficient income throughout their remaining years. Consequently, older individuals are exposed to heightened vulnerability concerning both economic insecurity and poverty, with limited avenues for escaping this predicament.

9. ROBUSTNESS ANALYSIS

To ensure the robustness of our results, we consider two kinds of alternative specifications:

9.1. Alternative weightings

In addition to the baseline calculation which assumes equal weights for all dimensions, here we use three alternative weighting structures by allocating 50% of the relative weight to one of the three dimensions, while distributing 25% to each of the other two dimensions (Alkire & Santos, 2014; Alkire & Fang, 2019; Alkire *et al.*, 2019). The marginal effects derived from our panel logit model estimations for the various weighting structures are shown in Table 6:

TABLE 6

MARGINAL EFFECTS FROM PANEL LOGIT ESTIMATION UNDER DIFFERENT WEIGHTING STRUCTURES (K=0.33)

	Multidimensional poverty (k = 0.33)							
	Equal weights (baseline model)		Education (½, ¼, ¼)		Health (¼, ½, ¼)		Living conditions (¼, ¼ , ½)	
	β	SE	*β*	SE	*β*	SE	*β*	SE
Rural woman	11.3009*	0.5095	3.1456*	0.2371	13.1205*	0.7809	25.7487*	0.5305
Indigenous	3.5578*	0.3394	1.0673*	0.1495	3.3170*	0.4872	4.5290*	0.3684
Mixed-race (mestizo)	-1.7122*	0.3334	-0.2188	0.1445	-2.0008*	0.4646	-2.9587*	0.3694
Primary school	37.2261*	0.1795	15.6920*	0.3259	31.6328*	0.3447	36.5571*	0.2057
University/ technical school	-7.0403*	0.5092	-1.5754*	0.2545	-6.1082*	0.5142	-10.7462*	0.7080
Master/ PhD	-13.9078*	2.1969	-2.7700*	1.2527	-12.9547*	1.4012	-24.4606*	4.3372
Public education	0.6444	0.3941	-0.0621	0.1793	1.3659*	0.4952	-2.7549*	0.4383
Unemployed	3.3617*	0.8321	0.2761	0.3814	6.2616*	1.0528	2.1055*	1.0509
Informal sector	6.9108*	0.3129	1.5670*	0.1443	7.9323*	0.3963	12.8974*	0.3615
No credit card	9.1483*	1.6286	1.8749*	0.7348	6.9096*	1.3856	12.453*	2.1682
Before pandemic	-7.7328*	1.6288	-1.1978	0.7340	-3.2020*	1.3836	-9.8214*	2.1691
COVID-19 outbreak	0.8531*	0.3332	0.3519*	0.1417	3.2848*	0.4571	3.1643*	0.3695
After pandemic	-0.1711	0.3313	-0.0227	0.1405	1.4597*	0.4553	0.5310	0.3634
Male	4.1246*	0.3221	1.4784*	0.1489	-0.9504*	0.4181	15.0292*	0.3845
Married	-1.0080*	0.2871	-0.4705*	0.1233	-1.8414*	0.3946	-1.1506*	0.3172
Age	-0.0789	0.0506	-0.0588*	0.0218	0.3841*	0.0703	-0.1743*	0.0556
Age squared	0.0025*	0.0005	0.0009*	0.0002	0.0007	0.0007	0.0021*	0.0005

Note: *p<0.05. SE: Standard Error.

Signs and statistical significance of the effects are consistently maintained across most cases. Given this, under most of the considered weighting structures it is found that there is a significantly heightened probability of experiencing multidimensional

poverty for specific groups such as rural women, indigenous individuals, those with only primary school education, the unemployed, informal workers, and those without access to credit cards. This pattern is similarly observed in the context of the COVID-19 outbreak, contributing to an increased likelihood of multidimensional poverty in all scenarios. Conversely, a reduced likelihood is found under most weighting structures for individuals of mestizo ethnicity, married individuals, and those with a university degree, technical education, or postgraduate studies.

However, regarding the effect of studying in a public institution, the sign varies across different weighting structures, which suggests that the assumed inferiority of the quality of public education with respect to private education may not be universal. This is because, as highlighted by Marcos and Vásquez (2018), the quality of private education varies widely based on the socioeconomic conditions of students and their families. Hence, higher enrollment costs in private schools tend to yield better student outcomes, while lower costs may result in comparable or even inferior results compared to peers in public institutions. Similarly, the signs and statistical significance of the variable capturing the post-effects of the pandemic are not consistent. Notably, the coefficient is positive and statistically significant only when greater importance is assigned to the health dimension. This may be attributed to the association of chronic diseases such as renal, cardiovascular, and respiratory conditions, diabetes, and cancer with severe COVID-19 outcomes (Gwavuya, 2020; Almeida *et al.*, 2021; Alyammahi *et al.*, 2021). Consequently, individuals with these preexisting conditions remain more vulnerable in terms of health and are more likely to experience multidimensional poverty even after the pandemic peak has subsided.

9.2. Alternative cutoffs

Here we explore alternative poverty cutoffs, specifically 30% and 35%, as suggested by Alkire and Apablaza (2016) and Thusitha *et al.* (2019). The marginal effects derived from our panel logit model estimations for the different thresholds are presented in Table 7.

Most variables maintain their signs and statistical significance across different cutoffs, except for the type of educational institution, which confirms our finding regarding that the assumed superiority of private over public education is not robust since there are very different levels of quality of private education depending on the socio-economic context. Additionally, factors such as the supply of private education should be considered, as in many rural localities only public education is available, which could affect comparisons between private and public schooling in those areas. According to Rojas (2019), 61% of public schools in Peru serve rural populations. These institutions often lack access to the Internet mobile phones, and basic services such as drinking water and drainage systems. Furthermore, in some cases students must walk between one and three hours to attend school. In this context, the propensity for experiencing multidimensional poverty is notably heightened for individuals with

TABLE 7

MARGINAL EFFECTS FROM PANEL LOGIT ESTIMATION UNDER DIFFERENT MULTIDIMENSIONAL CUTOFFS (EQUAL WEIGHTS)

	Multidimensional poverty					
	30		33 (baseline model)		35	
	β	SE	β	SE	β	SE
Rural woman	15.6649*	0.5696	11.3009*	0.5095	16.2657*	0.5164
Indigenous ethnicity	4.4861*	0.3626	3.5578*	0.3394	3.8794*	0.3447
Mixed-race (mestizo)	-1.9097*	0.3511	-1.7122*	0.3334	-2.0278*	0.3415
Primary school	39.7416*	0.1859	37.2261*	0.1795	37.1253*	0.1656
University/ technical school	-7.3769*	0.4515	-7.0403*	0.5092	-7.8893*	0.5917
Master/ PhD	-14.2723*	1.8855	-13.9078*	2.1969	-18.6668*	3.3372
Public education	2.1845*	0.4082	0.6444	0.3941	-1.0648*	0.4077
Unemployment	3.8195*	0.8192	3.3617*	0.8321	2.9157*	0.8981
Informal sector	8.9445*	0.3125	6.9108*	0.3129	8.9652*	0.3269
No credit card	10.7921*	1.5638	9.1483*	1.6286	9.6517*	1.8074
Before pandemic	-8.5917*	1.5639	-7.7328*	1.6288	-7.1686*	1.8079
COVID-19 outbreak	2.1043*	0.3456	0.8531*	0.3332	2.2436*	0.3435
After pandemic	0.3370	0.3441	-0.1711	0.3313	0.1636	0.3399
Male	5.7000*	0.3271	4.1246*	0.3221	7.5505*	0.3392
Married	-1.4588*	0.2988	-1.0080*	0.2871	-1.2039*	0.2958
Age	-0.2577*	0.0516	-0.0789	0.0506	-0.0328	0.0519
Age squared	0.0036*	0.0005	0.0025*	0.0005	0.0018*	0.0005

Note: *p<0.05. SE: Standard Error.

only primary schooling, rural women, those lacking access to a credit card, and those engaged in informal work. Conversely, higher education attainment, such as a university or postgraduate degree, diminishes the likelihood of experiencing multidimensional poverty, particularly under the 35% threshold.

10. CONCLUSIONS

Based on the structure of global MPI, we choose three dimensions -education, health, and living standards- to construct our ENAHO-based MPI. Then, we assess the determinants of both multidimensional and monetary poverty in Peru during the period 2019-2022 by employing logistic panel regressions with random effects.

In terms of temporal dynamics, we find that both monetary and multidimensional poverty experienced a rise during the COVID-19 outbreak. This increase is particularly pronounced in monetary poverty, which rose from 21% in 2019 to nearly 30% in 2020, given that most of the Peruvian workforce is engaged in the informal sector and is heavily reliant on daily earnings, making them particularly vulnerable to quarantines.

Conversely, the indicators constituting multidimensional poverty tend to exhibit relative stability over time since they are related to individual and household characteristics that are difficult to change, at least in the short run, which explains why this rate increased slightly from 27.56% to 27.75% between 2019 and 2020. For instance, if a person lacked access to drinking water before the pandemic, it is likely that this deprivation persists during and after the COVID-19 outbreak. Also, the measures undertaken by the Peruvian government's social assistance programs in response to the pandemic, such as the distribution of food baskets, played an important role in alleviating the adverse effects of the health crisis on multidimensional poverty.

Concerning the determinants of poverty, our analysis of individual and household characteristics reveals a consistent pattern in the signs and statistical significance of the marginal effects for both monetary and multidimensional poverty across most weighting structures and poverty cutoffs (30%, 33% and 35%). Notably, certain demographic groups exhibit a significantly heightened probability of experiencing both monetary and multidimensional poverty, such as rural women, those with only primary school education, the unemployed and informal workers. For example, individuals with only primary education are 37% and 12% more likely to experience both multidimensional and monetary poverty, respectively. Similarly, the likelihood of experiencing both multidimensional and monetary poverty was heightened due to the COVID-19 outbreak across all poverty cutoffs and weighting structures, particularly in the scenario where more importance was assigned to the health dimension.

However, the effects of the COVID-19 outbreak have lingered over time even after the emergency state ended and economic activities resumed. In this sense, we have found that individuals were 33% less likely to experience monetary poverty in 2019, but that this probability decreased to only 3% in the year following the COVID-19 outbreak. In the same lines, a diminished likelihood of experiencing both types of poverty is found among individuals of mestizo ethnicity and those with a university degree, technical education, or postgraduate studies. For example, individuals with a master's or PhD degree experience a 14% and 39% lower likelihood of facing multidimensional and monetary poverty, respectively. Nevertheless, the impact of studying in a public institution varies across different weighting structures and poverty cutoffs. This suggests that the presumed superiority of private education over public education is not necessarily robust since the quality of private education varies across different socio-economic contexts.

Based on these findings, it is strongly advised that, for the effective implementation of policy measures, the government should consider both monetary and multidimensional poverty as the weaknesses of one are often offset by the strengths of the other (Bautista, 2018). Regarding the determinants influencing poverty status, in line with the International Monetary Fund (2023), it is suggested that the Peruvian government should continue providing social transfers in times of economic downturn, with a special focus on rural women engaged in the informal sector as they are particularly vulnerable to poverty. Additionally, it is advisable for the government to implement

forms of unemployment protection, such as unemployment savings accounts and insurance, due to the heightened vulnerability of the unemployed to fall into poverty, particularly those in the informal sector. Lastly, in the realm of education, it is recommended that the government may introduce standardized tests, akin to the Scholastic Assessment Test (SAT). Such evaluations could serve as incentives for both public and private institutions, regardless of enrollment cost, to compete and enhance the quality of education.

APPENDIX A

Likelihood-ratio test

$$H_0: \rho = \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\varepsilon^2} = 0$$

$$H_1: \rho = \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\varepsilon^2} \neq 0$$

Prob >= chibar2 = 0.000

The null hypothesis of the likelihood-ratio test of $\rho = \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\varepsilon^2}$, which represents the proportion of the total variance attributed to the panel-level variance component, indicates that variance across individuals is equal to zero ($H_0: \rho = 0$), which implies that the panel estimator is no different from the pooled estimator. Since the p-value is smaller than 0.01, we reject the null hypothesis, concluding that random effects are necessary (StataCorp, n.d.).

APPENDIX B

Table 8 displays the marginal effects obtained from a panel logit model estimation that incorporates interactions with the 2020 dummy variable. Most statistical significance and signs remain consistent with those in the baseline model shown in *Table 5*. For example, individuals with postgraduate degrees are consistently less likely to experience both multidimensional and monetary poverty, regardless of the interaction with the COVID-19 outbreak. However, during the pandemic peak, those with a master's degree or PhD were even less likely to fall into multidimensional poverty compared to the scenario without the 2020 interaction. This could be attributed to their ability to easily transition to remote work due to access to services like the Internet and the nature of their jobs, which reduced their risk of job loss and provided protection from infection (World Bank, 2023). Additionally, the interaction terms between the COVID-19 outbreak and rural women, as well as those for people of indigenous ethnicity, were statistically significant in explaining the incidence of multidimensional poverty. This may be linked to the fact that the pandemic exacerbated existing territorial disparities and differences in the access to productive assets and public services among minorities (World Bank, 2023).

TABLE 8
MARGINAL EFFECTS FROM PANEL LOGIT ESTIMATION FOR MULTIDIMENSIONAL AND MONETARY POVERTY INCLUDING INTERACTION TERMS WITH THE COVID-19 OUTBREAK

	Dependent variable			
	Multidimensional poverty		Monetary poverty	
	β	SE	β	SE
Rural woman x COVID-19	9.6539*	0.9547	1.2607	1.0069
Indigenous ethnicity x COVID-19	2.8450*	0.5240	0.6865	0.6660
Mixed-race (mestizo)	-4.0366*	0.2617	-6.0942*	0.3600
Primary school	37.8420*	0.1844	11.9965*	0.3724
University/ technical school (completed)	-7.1977*	0.5131	-15.8112*	0.7767
Master/ PhD x COVID-19	-14.0252*	2.2195	-38.5288*	5.1344
Public education	0.2523	0.3892	-0.4267	0.4873
Unemployed	3.3605*	0.8469	7.9251*	1.1348
Informal	7.9131*	0.3544	8.4257*	0.5028
Informal sector x COVID-19	-0.1995	0.6202	-1.0894	0.8536
No credit card	9.6563*	1.6447	29.5029*	4.1455
Before pandemic	-8.3385*	1.6447	-32.8121*	4.1435
COVID-19 outbreak	-0.9340	0.5839	1.3380	0.8119
After pandemic	-0.1017	0.3315	-2.5413*	0.4409
Male	1.4924*	0.2955	5.8571*	0.4006
Married	-0.8440*	0.2906	3.6197*	0.3798
Age	-0.1087*	0.0507	-0.9497*	0.0647
Age squared	0.0028*	0.0005	0.0059*	0.0006

Note: *p<0.05. SE: Standard Error.

REFERENCES

ADETORO, A.; NGIDI, M.; DANSO-ABBEAM, G. (2023). Towards the global zero poverty agenda: Examining the multidimensional poverty situation in South Africa. *SN Social Sciences, 3*(148). https://doi.org/10.1007/s43545-023-00735-2

AGARWAL, B. (1989). Rural women, poverty and natural resources: Sustenance, sustainability and struggle for change. *Economic and Political Weekly, 24*(43), WS46-WS65. http://www.jstor.org/stable/4395522

ALCÁZAR, L.; ROJAS, V. & LOPEZ, E. (2022). *Medidas de protección social del gobierno peruano en época de la COVID-19.* Fondo de las Naciones Unidas para la Infancia

ALKIRE, S, & SANTOS, M. (2014). Measuring acute poverty in the developing world: Robustness and scope of the Multidimensional Poverty Index. *World Development, 59,* 251-274. http://dx.doi.org/10.1016/j.worlddev.2014.01.026

ALKIRE, S. & APABLAZA, M. (2016). Multidimensional poverty in Europe 2006-2012: Illustrating a methodology. *Oxford Poverty and Human Development Initiative*, Working Paper No. 74. http://www.ophi.org.uk/multidimensional-poverty-in-europe-2006-2012-illustrating-a-methodology/

ALKIRE, S. & FANG, Y. (2019). Dynamics of multidimensional poverty and uni-dimensional income poverty: An evidence of stability analysis from China. *Social Indicators Research, 142*(1), 25-64. https://doi.org/10.1007/s11205-018-1895-2

ALKIRE, S. & FOSTER, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics, 95*(7-8), 476-487. https://doi.org/10.1016/j.jpubeco.2010.11.006

ALKIRE, S. & SHEN, Y. (2017). Exploring multidimensional poverty in China: 2010 to 2014. *Research on Economic Inequality, 25,* 161-228. https://doi.org/10.1108/S1049-258520170000025006

ALKIRE, S., FOSTER, J. E., SETH, S., SANTOS, M. E., ROCHE, J. M., & BALLON, P. (2015). Multidimensional Poverty Measurement and Analysis. *University of Leeds*, Research Paper No. 15. https://ssrn.com/abstract=2564787

ALKIRE, S.; KANAGARATNAM, U.; NOGALES, R. & SUPPA, N. (2019). Sensitivity analyses in poverty measurement: The case of the Global Multidimensional Poverty Index. *Oxford Poverty & Human Development Initiative*, Working Paper. https://ora.ox.ac.uk/objects/uuid:95e0828f-4365-4dc8-8850-af2a13892ce7

AL-MAMUN, A., & MAZUMDER, M. N. H. (2015). Impact of microcredit on income, poverty, and economic vulnerability in Peninsular Malaysia. *Development in Practice, 25*(3), 333–346. https://doi.org/10.1080/09614524.2015.1019339

ALMEIDA, P.; DIAS, S.; GAMA, A.; MONIZ, M.; PEDRO, A.; SOARES, P.; AGUILAR, P. & NUNES, C. (2021). The association between chronic disease and serious COVID-19 outcomes and its influence on risk perception: Survey study and database analysis. *JMIR Public Health Surveill, 7*(11). https://doi.org/10.2196/22794

ALYAMMAHI, S.; ABDIN, S.; ALHAMAD, D.; ELGENDY, S.; ALTELL, A.; OMAR, H. (2021) The dynamic association between COVID-19 and chronic disorders: An updated insight into prevalence, mechanisms and therapeutic modalities. *Infection, Genetics and Evolution, 87*. https://doi.org/10.1016/j.meegid.2020.104647

BANERJEE, A. & DUFLO, E. (2011). *Repensar la pobreza. Un giro radical en la lucha contra la desigualdad global*. Taurus.

BAUTISTA, C. (2018). Explaining multidimensional poverty: A household-level analysis. *Asian Economic Papers, 17*(3), 183-210. https://doi.org/10.1162/asep_a_00648

BETTI, G.; D'AGOSTINO, A. & NERI, L. (2002). Panel regression models for measuring multidimensional poverty dynamics. *Statistical Methods & Applications, 11*, 359-369. https://doi.org/10.1007/BF02509832

CANELAS, C. (2018). Informality and poverty in Ecuador. *Small Business Economics, 53*, 1097-1115. https://doi.org/10.1007/s11187-018-0102-9

CENTER ON BUDGET AND POLICY PRIORITIES. (2022, February the 10th). *Tracking the COVID-19 Economy's Effects on Food, Housing, and Employment Hardships*. https://www.cbpp.org/research/poverty-and-inequality/tracking-the-covid-19-economys-effects-on-food-housing-and

CHEN, K. & WANG, T. (2015). Determinants of poverty status in Taiwan: A multilevel approach. *Social Indicators Research, 123*(2), 371-389. https://doi.org/10.1007/s11205-014-0741-4

CLAUSEN, J. & BARRANTES, N. (2020). Implementing a group-specific multidimensional poverty measure: The case of persons with disabilities in Peru. *Journal of Human Development and Capabilities, 21*(4), 355-388. https://doi.org/10.1080/19452829.2020.1828316

COONTZ, S. & FOLBRE, N. (2002, April the 28th). *Marriage, poverty and public policy*. University of Texas at Austin, https://sites.utexas.edu/contemporaryfamilies/2002/04/28/marriage-poverty-public-policy-brief/

CORCORAN, M. & HILL, M. (1980). Unemployment and poverty. *Social Service Review, 54*(3), 407-413. https://www.jstor.org/stable/30015846

COROMALDI, M. & ZOLI, M. (2012). Deriving multidimensional poverty indicators: Methodological issues and an empirical analysis for Italy. *Social Indicators Research, 107*, 37-54. https://doi.org/10.1007/s11205-011-9825-6

COVARRUBIAS, A. (2023). Gender and multidimensional poverty at the individual level in Mexico. *Development Studies Research, 10*(1), 1-12. https://doi.org/10.1080/21665095.2023.2218577

CUENCA, A. & CAMARGOS, E. (2022). Effect of the COVID-19 pandemic on multidimensional poverty in Paraguay during the 2016-2020 period. *Revista de Economía del Caribe,* (29), 11-31. https://doi.org/10.14482/ecoca.29.003.499

ESCOBAL, J. (2012). Multidimensional poverty and inequality of opportunity in Peru: Taking advantage of the longitudinal dimension of Young Lives. *Young Lives*, Working Paper No. 79. https://www.ninosdelmilenio.org/wp-content/uploads/2012/10/wp79.pdf

FUENTES, Y. (2014). *The effects of credit cards on low-income populations* [Master thesis]. Humboldt State University. https://scholarworks.calstate.edu/downloads/3t945s95d

GALINDO, M.; FUENTES, C.; ALCANTARA, M.; MARTINEZ, A. (2022, October the 4th). *Multidimensional poverty in Mexico in the context of the COVID-19 health emergency*. Multidimensional Poverty Peer Network, https://www.mppn.org/multidimensional-poverty-in-mexico-in-the-context-of-the-COVID-19-health-emergency/

GALLARDO, M. (2022). Measuring vulnerability to multidimensional poverty with Bayesian network classifiers. *Economic Analysis and Policy, 73*, 492-512. https://doi.org/10.1016/j.eap.2021.11.018

GAMBETTA, R. (2007). Poverty dynamics in Peru 2001-2003: A probit model analysis. *University of Munich*, Working Paper No. 3723. https://mpra.ub.uni-muenchen.de/3723/1/MPRA_paper_3723.pdf

GWAVUYA, S. (2020). How the pandemic will aggravate multidimensional poverty in Afghanistan. *Dimensions*, (10), 19-22. https://www.mppn.org/wp-content/uploads/2020/08/EN-Dimension-10_WEB-6.pdf

HINTEREGGER, T. (2017, October the 3rd). *A Global Dilemma: How Unemployment Creates Poverty.* https://www.borgenmagazine.com/unemployment-creates-poverty/

INFECTION, GENETICS AND EVOLUTION,SIMIYU, S.; CAIRNCROSS, S. & SWILLING, M. (2018). Understanding living conditions and deprivation in informal settlements in Kisumu, Kenya. *Urban Forum, 30,* 223-241. https://doi.org/10.1007/s12132-018-9346-3

INSTITUTO NACIONAL DE ESTADISTICA E INFORMATICA. (2015). *Perú: Encuestas panel*. Instituto Nacional de Estadística e Informática.

INSTITUTO NACIONAL DE ESTADISTICA E INFORMATICA. (2022a). *Definición y uso de los valores monetarios de la base de datos 2022*. Instituto Nacional de Estadística e Informática.

INSTITUTO NACIONAL DE ESTADISTICA E INFORMATICA. (2022b). *Ficha técnica: Encuesta Nacional de Hogares 2022*. Instituto Nacional de Estadística e Informática.

INSTITUTO NACIONAL DE ESTADISTICA E INFORMATICA. (2023*). Perú: Evolución de la pobreza monetaria 2011-2022*. Instituto Nacional de Estadística e Informática.

INSTITUTO PERUANO DE ECONOMIA. (2021, 6 de julio). *Efectos del COVID-19 en la educación*. https://www.ipe.org.pe/portal/efectos-del-COVID-19-en-la-educacion/

INTERNATIONAL MONETARY FUND. (2023). *Income Volatility and Social Insurance in Latin America (Background Paper 1).* https://www.imf.org/-/media/Files/Publications/REO/WHD/2023/October/English/background-paper-1-en.ashx

KHAN, M.; SABOOR, A.L; RIZWAN, M. & AHMAD, T. (2020). An empirical analysis of monetary and multidimensional poverty: Evidence from a household survey in Pakistan. *Asia Pacific Journal of Social Work and Development, 30*(2), 106-121. https://doi.org/10.1080/02185385.2020.1712663

KOHLER, U. & KREUTER, F. (2012). *Data Analysis Using Stata [3rd ed.].* Stata Press.

LIN, Y.; ZHU, K.; YAO, Q.; LI, J.; CAI, J.; HE, T. & PING, H. (2021). Impact of the COVID-19 pandemic on farm households' vulnerability to multidimensional poverty in rural China. *Sustainability, 13*(4). https://doi.org/10.3390/su13041842

MARCOS, M. & VASQUEZ, M. (2018). Tipología y caracterización de las escuelas privadas en el Perú. *Ministerio de Educación*, Estudios Breves No. 3, http://umc.minedu.gob.pe/wp-content/uploads/2019/01/EB03.pdf

MINISTERIO DE DESARROLLO E INCLUSION SOCIAL. (2023, 27 de julio). *Decreto Supremo No. 002-2023-MIDIS*. https://www.gob.pe/institucion/midis/normas-legales/4597514-002-2023-midis

MUÑOZ, A.; BUITRAGO, P.; DE LA BRIERE, B.; NEWHOUSE, D; RUBIANO, E., SCOTT, K. & SUAREZ-BECERRA, P. (2018). Gender differences in poverty and household composition through the life-cycle: A global perspective. *World Bank Group*, Working Paper No. 8360. https://documents1.worldbank.org/curated/en/135731520343670750/pdf/WPS8360.pdf

NORSTRÖM, F.; WAENERLUND, A.; LINDHOLM, L.; NYGREN, R.; SAHLEN, K. & BRYDSTEN, A. (2019). Does unemployment contribute to poorer health-related quality of life among Swedish adults? *BMC Public Health, 19*(457). https://doi.org/10.1186/s12889-019-6825-y

OBOLER, S. & CALLIRGOS, J. (2015). *El racismo peruano*. Ministerio de Cultura y Dirección Desconcentrada de Cultura de Cusco.

OLARINDE L.; ABASS A.; ABDOULAYE, T.; ADEPOJI, A.; GBENGA, E.; OLUFEMI, M.; ADEKUNIE, O. & WASIU, A. (2020) Estimating multidimensional poverty among Cassava producers in Nigeria: patterns and socioeconomic determinants. *Sustainability, 12*(13). https://doi.org/10.3390/su12135366

ORGANISATION FOR ECONOMIC CO-OPERATION AND DEVELOPMENT. (2023). *Estudios Económicos de la OECD: Perú 2023*. https://doi.org/10.1787/f67c8432-es

PENG, Y. (2022). Multidimensional relative poverty of rural women: Measurement, dynamics, and influencing factors in China. *Frontiers in Psychology, 13*, 1-15. https://doi.org/10.3389/fpsyg.2022.1024760

QUISPE-MAMANI, J.; AGUILAR-PINTO, S.; CALCINA-ÁLVAREZ, D.; ULLOA-GALLARDO, N.; MADUEÑO-PORTILLA, R.; VARGAS-ESPINOZA, J.; QUISPE-MAMANI, F.; CUTIPA-QUILCA, B.; TAIRO-HUAMAN, R. & COACALLA-VARGAS, E. (2022). Social factors associated with poverty in households in Peru. *Social Sciences, 11*(12). https://doi.org/10.3390/socsci11120581

ROJAS, A. (2019, December 5). En el Perú hay más colegios rurales pero adolecen de servicios básicos, infraestructura y docentes. *El Comercio*. https://elcomercio.pe/peru/en-el-peru-hay-mas-colegios-rurales-pero-adolecen-de-servicios-basicos-infraestructura-y-docentes-noticia/?ref=ecr

RUGGERI, C. (1999). The many dimensions of deprivation in Peru: Theoretical debates and empirical evidence. *Queen Elizabeth House* [University of Oxford], Working Paper No. 29. http://workingpapers.qeh.ox.ac.uk/RePEc/qeh/qehwps/qehwps29.pdf

SANCHEZ, R.; MANZANO, L. & MATURANA, L. (2022). Labor informality and monetary and multidimensional poverty in Bogotá and the Metropolitan Area. *Problemas del desarrollo, 53*(208), 31-63. https://doi.org/10.22201/iiec.20078951e.2022.208.69754

SANTOS, M. (2019). Challenges in designing national multidimensional poverty measures. *Economic Commission for Latin America and the Caribbean*, Working Paper No. 100. https://www.cepal.org/sites/default/files/publication/files/44453/S1801163_en.pdf

SANTOS, M. VILLATORO, P.; MANCERO, X. & GERSTENFELD, P. (2015). A Multidimensional Poverty Index for Latin America. *Oxford Poverty & Human Development Initiative*, Working Paper No. 79. https://www.ophi.org.uk/wp-content/uploads/OPHIWP079.pdf

SEN, A. (1999). *Desarrollo y libertad*. Editorial Planeta.

SOCIEDAD NACIONAL DE INDUSTRIAS. (2022). *Perú regiones al 2031*. https://sni.org.pe/wp-content/uploads/2022/08/LIBRO-PERU-REGIONES-AL-2031.pdf

STATACORP. (n.d.). *xtlogit – Fixed-effects, random-effects, and population-averaged logit models*. StataCorp.

THANH, H.; THU, H.; THANH, N.; MINH, T. & THANH, H. (2022). The effect of financial inclusion on multidimensional poverty: The case of Vietnam. *Financial economics, 10*(1), 1-22. https://doi.org/10.1080/23322039.2022.2132643

THUSITHA, K.; SAMARAWEERA, R. & DHARMADASA, S. (2019). Multidimensional poverty among the estate population of Badulla District in Sri Lanka. *Sri Lanka Journal of Population Studies, 20*(2), 43-62. http://www.erepo.lib.uwu.ac.lk/bitstream/handle/123456789/151/113.pdf?sequence=1&isAllowed=y

TORRES-REYNA, O. (2007). *Panel Data Analysis Fixed and Random Effects using Stata (v. 6.0).* Princeton University.

UNITED NATIONS DEPARTMENT OF ECONOMIC AND SOCIAL AFFAIRS (2015). *Income poverty in old age: An emerging development priority*. https://www.un.org/esa/socdev/ageing/documents/PovertyIssuePaperAgeing.pdf

UNITED NATIONS EDUCATIONAL, SCIENTIFIC AND CULTURAL ORGANIZATION. (2010). *Reaching the marginalized*. Oxford University Press.

UNITED NATIONS. (2023). *The Sustainable Development Goals Report. Special edition*. https://unstats.un.org/sdgs/report/2023/The-Sustainable-Development-Goals-Report-2023.pdf

URBINA, D. & QUISPE, M. (2017). La pobreza monetaria desde la perspectiva de la pobreza multidimensional: el caso peruano. *Enfoque,* (2), 77-98. https://hdl.handle.net/20.500.12724/5815

VASQUEZ, E. (2012). El Perú de los pobres no visibles para el Estado: La inclusión social pendiente a julio del 2012. *Universidad del Pacífico*, Documento de Discusión No. DD/12/04. https://repositorio.up.edu.pe/handle/11354/383

VELA, L.; FERANDEZ, A.; REYNOSA, E.; LLONTO, Y.; DAVILA, J. & HERRERA, J. (2023). A psychilogical study in determinants of poverty in Peru: COVID-19 context. *Journal for Re Attach Therapy and Developmental Diversities, 6*(5). 799-816. https://jrtdd.com/index.php/journal/article/view/633

WORKNEH, M. & ESHETE, Z. (2020). Household level non-monetary poverty in Ethiopia and its driving factors: a multidimensional approach with panel estimation. *Social Indicators Research, 154*, 145-168. https://doi.org/10.1007/s11205-020-02569-4

WORLD BANK. (2023). *Resurgir fortalecidos: Evaluación de pobreza y equidad en el Perú.* Grupo Banco Mundial.

YANG, F.; JIANG, Y. & PAUDEL, K. (2021). Impact of credit constraints from forma financial institutions on rural resident's health in China. *Healthcare, 9*(1). 10.3390/healthcare9010006

ACKNOWLEDGMENTS

We would like to express our gratitude to the members of the *Círculo de Estudios de Desarrollo Económico y Social* of the University of Lima since their comments contributed to the improvement of this paper.

DECLARATIONS

Competing Interest. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to infuence the work reported in this paper.

Open Access. This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article

are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

AUTHOR CONTRIBUTIONS

Conceptualization: Nicole Ariana Cáceres Bautista, Dante A. Urbina; Methodology: Nicole Ariana Cáceres Bautista, Dante A. Urbina; Formal analysis and investigation: Nicole Ariana Cáceres Bautista, Dante A. Urbina; Writing - original draft preparation: Nicole Ariana Cáceres Bautista; Writing - review and editing: Nicole Ariana Cáceres Bautista, Dante A. Urbina.